

# Draw Step by Step: Reconstructing CAD Construction Sequences from Point Clouds via Multimodal Diffusion.

## Supplementary Material

### 1. Overview

In the supplementary material, we will first briefly introduce the basics of diffusion strategy in discrete token domains. The details of the point cloud tokenizer will be introduced next. After that, the evaluation metrics and details of the compared methods in the experiments will be introduced. Finally, more qualitative and quantitative results, along with the user study and ablation study, will be produced to further demonstrate the effectiveness of our proposed method.

### 2. Supplementary of the Token-based Diffuser

#### 2.1. Discrete Diffusion on Tokens

For diffusion on tokens, each token lies in discrete domains where *middle states* are hardly interpretable. For tokens, each token in  $x_t$  is a discrete random variable with  $N$  categories, where  $N = |V| = \sum |V_i|$  is the sum of vocabulary size in all modalities.  $x_t$  can be represented as a stack of one-hot vectors on the unions of vocabularies of different modalities. The forward process can be defined as

$$q(x_t|x_{t-1}) = \text{Cat}(x_t; p = x_{t-1}Q_t), \quad (1)$$

where  $\text{Cat}(\cdot)$  is a categorical distribution and  $Q_t$  is a transition matrix on tokens. Each token is operated independently by  $Q_t$  where  $[Q_t]_{i,j} = q(x_t = j|x_{t-1} = i)$ . It can be derived that

$$\begin{aligned} q(x_{t-1}|x_t, x_0) &= \frac{q(x_t|x_{t-1}, x_0)q(x_{t-1}|x_0)}{q(x_t|x_0)} \\ &= \text{Cat}(x_{t-1}; p = \frac{x_t Q_t^T \odot x_0 \prod_{i=1}^{t-1} Q_i}{x_0 \prod_{i=1}^t Q_i x_i^T}), \end{aligned} \quad (2)$$

where  $\odot$  is elementwise multiplication and the division is row-wise.

When we put  $q(x_t|x_{t-1})$  into

$$\begin{aligned} L_{vib} &= E_q[D_{KL}(q(x_T|x_0)||p_\theta(x_T))] \\ &+ E_q[\sum_{t=2}^T D_{KL}(q(x_{t-1}|x_t, x_0)||p_\theta(x_{t-1}|x_t, t))] \\ &- \log p_\theta(x_0|x_1), \end{aligned} \quad (3)$$

which is introduced in the main paper, we can use a model  $p_\theta(x_{t-1}|x_t, x_0)$  to learn the reverse process.

#### 2.2. Decoding Details of the Reverse Process

The reverse process can be regarded as an iterative decoding process guided by the noise schedule. During inference,

all tokens are predicted first, and noised are added back like DDIM. For sampling of each token, we utilize MBR decoding technique which selects tokens of the largest utility, namely Minimizing the Baye’s Risk of the entire generated set. For sampling techniques, we adopt top-K sampling. The most promising result will be selected unless specially mentioned. MBR decoding, top-K sampling as well as the diffusion process contribute to the reconstruction fidelity and diversity as a whole.

### 3. Details of Point Cloud Tokenizer

In this part we will put forward the network architecture of the point cloud tokenizer. The tokenizer is composed of an encoder, a decoder and a feature propagator. The encoder is a 5-layer DGCNN along with 2 convolution layers. The decoder is a 5-layer DGCNN along with 2 convolution layers. The feature propagator is a 3 layer DGCNN whose input is the output of the 2nd layer of DGCNN in the decoder. The codebook is of size 8192.

### 4. Experiment Details

#### 4.1. Details of evaluation metrics

In this part we will introduce the evaluation metrics used in the reconstruction accuracy and generation diversity.

For the metrics used in reconstruction, the introduction is as follows.

**Command Accuracy.** Command Accuracy  $ACC_{ct}$  measures the correctness of the predicted CAD primitive type  $t$ , as is defined as

$$ACC_{ct} = \frac{1}{N_c} \sum_{i=1}^{N_c} \mathbb{1}[t_i = \hat{t}_i], \quad (4)$$

where  $N_c$  denotes the total number of primitive,  $t_i$  and  $\hat{t}_i$  are the ground truth and reconstructed primitive types, and  $\mathbb{1}[\cdot]$  is the indicator function with value 0 or 1. Following DeepCAD, we truncate or pad the reconstructed sequences to make the predicted and ground truth sequences of the same length.

**Parameter Accuracy.** Parameter Accuracy  $ACC_{cp}$  is calculated when commands are successfully predicted. The formal definition of  $ACC_{cp}$  is

$$ACC_{cp} = \frac{1}{K} \sum_{i=1}^{N_c} \sum_{j=1}^{|\hat{p}_i|} \mathbb{1}[|p_{i,j} - \hat{p}_{i,j}| < \eta] \mathbb{1}[t_i = \hat{t}_i], \quad (5)$$

where  $K = \sum_{i=1}^{N_c} \mathbb{1}[t_i = \hat{t}_i] \cdot |p_i|$ , symbolizing the total number of parameters in all of the correctly predicted commands.  $\eta$  is the tolerance threshold. Following the original setting of DeepCAD, all parameters are quantized into 8 bits, namely in range  $0 \sim 255$  and the threshold is set as  $\eta = 3$  to make fair comparisons.

**Chamfer Distance** Chamfer distance is a common metric for 3D shape reconstruction and generation. Following DeepCAD, we uniformly sample 2000 points from the *rendered shape of the reconstructed construction sequence* and the shape of the ground truth CAD construction sequence. We measure the chamfer distance between the two sets of points.

**IoU** IoU (Intersection over Union) is another common metric for 3D shape reconstruction and generation. We use PythonOCC to convert the *rendered shape of the reconstructed construction sequence* and the shape of the ground truth CAD construction sequence into mesh and use python package trimesh to calculate their IoU.

**IR** IR (Invalid Rate) stand for CAD sequences that cannot be rendered as a valid 3D shape in finite time. Here all reconstructed shapes are rendered via PythonOCC with a fixed time limit of 5 minutes. All sequences that are not able to be rendered into geomrtry in such time limit are regarded as invalid.

**# $\Delta P$**  # $\Delta P$  is an auxiliary metric of reconstructed sequence fidelity that measures the difference of length between the reconstructed sequence and the ground truth sequence. As  $ACC_{ct}$  cannot symbolize the length difference, this metric serves as another perspective to measure the likeliness between the reconstructed and ground truth sequence. The formal definition of # $\Delta P$  is as follows

$$\#\Delta P = |N_c - \hat{N}_c|, \quad (6)$$

where  $N_c$  is the total number of ground truth primitives while  $\hat{N}_c$  the total number of primitives in the predicted sequence.

The **Chamfer Distance** and **IoU** serve as the fidelity for the geometry of the reconstructed sequence, while the **Command Accuracy**, **Parameter Accuracy** and # $\Delta P$  not only serve as an indicator of the accuracy of reconstructed construction sequences, but also shows whether the reconstructed sequences are concise and whether useless entities are introduced, which measures the extent that the reconstructed sequences are easily modifiable and reusable by the side.

For the metrics used in measuring generation diversity, the introduction is as follows.

Following previous works like DeepCAD and HNC-CAD, we both measure the diversity and fidelity of rendered geometric shape of the generated CAD construction sequences, and we measure the diversity of the generated CAD construction sequences itself.

**Coverage (COV)** measures diversity of rendered geometric shape of the generated CAD construction sequences. It represents the proportion of the shape in the reference set  $\mathcal{S}$  that serve as the nearest neighbor of the generated set  $\mathcal{G}$ , which is formally defined as

$$\text{COV}(\mathcal{S}, \mathcal{G}) = \frac{|\{\arg \min_{Q \in \mathcal{S}} d^{CD}(P, Q) | P \in \mathcal{G}\}|}{|\mathcal{S}|}, \quad (7)$$

where  $d^{CD}(P, Q)$  represents the chamfer distance between two point clouds  $P$  and  $Q$ .

**Minimum Matching Distance (MMD)** serves as an auxiliary metric of COV which measures the fidelity of generated shapes. It calculates the chamfer distance of a shape in the generated set  $\mathcal{G}$  to its nearest neighbor in the reference set  $\mathcal{S}$ . We measure the average of all nearest distances as follows.

$$\text{MMD}(\mathcal{S}, \mathcal{G}) = \frac{1}{|\mathcal{S}|} \sum_{Q \in \mathcal{S}} \min_{P \in \mathcal{P}} d^{CD}(P, Q). \quad (8)$$

**Jenson Shannon Divergence (JSD)** JSD is a statistical distance metric between data distributions, which measures the similarity between reference set  $\mathcal{S}$  and generated set  $\mathcal{G}$  by computing marginal point distributions as follows

$$\text{JSD}(P_{\mathcal{S}}, P_{\mathcal{G}}) = \frac{1}{2} D_{KL}(P_{\mathcal{S}} \| M) + \frac{1}{2} D_{KL}(P_{\mathcal{G}} \| M), \quad (9)$$

where  $M = \frac{1}{2}(P_{\mathcal{S}} + P_{\mathcal{G}})$  and  $D_{KL}$  is the standard KL-divergence.  $P_{\mathcal{S}}$  and  $P_{\mathcal{G}}$  are marginal distributions of points in reference sets calculated by approximating the point cloud sets into voxels of size  $28 * 28 * 28$  and assigning each point into one of the voxels.

**Novelty** This metric measures the proportion of generated CAD sequences that does not appear in the training set, following HNC-CAD.

**Unique** This metric measures the proportion of generated CAD sequences that appears only once in the generated set, following HNC-CAD.

**Token n-grams** This metric is calculated by measuring the count of distinct token n-grams in generated CAD sequence divided by numbefr of tokens.

**Embedding Similarity** This metric is calculated by encoding all generated CAD sequences via pretrained DeepCAD encoder and calculate the averaged similarity between all embeddings in the generated set, which is shown as

$$\text{sim}(\mathcal{G}) = \frac{1}{|\mathcal{G}|} \frac{1}{|\mathcal{G}|} \sum_{X_i \in \mathcal{G}} \sum_{X_j \in \mathcal{G}} \frac{E(X_i)E(X_j)}{|E(X_i)||E(X_j)|}, \quad (10)$$

where  $E$  represents the DeepCAD encoder while  $X_i$  and  $X_j$  are generated CAD sequences.  $|\mathcal{G}|$  is the size of  $\mathcal{G}$ .

**Edit Distance** This metric is calculated by measuring the edit distance between each two generated sequences in the

generated sets, which is shown as

$$\text{EDIT}(\mathcal{G}) = \frac{1}{|\mathcal{G}|} \frac{1}{|\mathcal{G}|} \sum_{X_i \in \mathcal{G}} \sum_{X_j \in \mathcal{G}} d^{\text{edit}}(X_i, X_j), \quad (11)$$

where  $d^{\text{edit}}$  represents the edit distance.  $|\mathcal{G}|$  is the size of  $\mathcal{G}$ .

In all, **Coverage (COV)**, **Coverage (MMD)** and **Coverage (JSD)** measures the diversity and the corresponding fidelity of the rendered shape in generated CAD sequences. **Novelty**, **Token n-grams**, **Embedding Similarity** and **Edit Distance** measures the diversity of generated CAD models at the sequence level.

## 4.2. Details of comparative methods

In this part we will briefly illustrate the method for implementing compared methods in our experiments.

**SECAD-Net** For SECAD-Net, we use the code and pretrained models provided in their open-sourced repository for testing. Note that the generated CAD sequences in their method are too long compared with the ground truth. We neglect all consecutive data points that remain the same after 8-bit tokenization and only retain the endpoints that stay in a straight line.

**Point2cyl** For Point2cyl, we use their open-sourced code and pretrained model for cylinder extrusion. However, as the paper and the open-sourced code does not provide methods for converting sketch into CAD construction sequences, we use the use the conversion method in SECAD-Net instead.

**ExtrudeNet** For ExtrudeNet, as the pretrained model is not provided, we used the open-sourced code for training. During testing, we first pick the sketch-extrusion pairs that really contribute to the final volume from all reconstructed sketch-extrusion pairs. Then for each sketch, we convert the Bezier curves into combinations of lines and arcs using de Casteljau algorithm.

**Lambourne’s method** There’s no open-sourced code for Lambourne’s method. We reimplement the method using the following steps. First, we train a classifier to classify which kind of the 18 extrusion combinations the model belongs to. We also train 18 independent segmenters and extrusion predictors for the corresponding combination. For sketch retrieval, we finetune a pretrained SEResNet on all retrieved sketches in DeepCAD datasets.

**DeepCAD** For DeepCAD, we use the code and pretrained models provided in their open-sourced repository for testing.

**HNC-CAD** For HNC-CAD, we use the generation method as our baseline and implement a point cloud feature extractor as the point cloud condition. The point cloud encoder is a modification of Point BERT and takes the place of the model encoder for auto-completion purpose in the original HNC-CAD implementation.

Method	JSD	Novel	Unique
<b>DeepCAD</b>	3.29	91.7	85.8
<b>SkexGen</b>	0.90	99.1	99.8
<b>HNC-CAD</b>	0.68	93.9	99.7
<b>Our Method</b>	2.42	97.3	98.6

Table 1. More results on generation diversity. We report test set JSD, Novel and Unique as supplementary. JSD is multiplied by  $10^2$ .

## 4.3. Quantitative results on generation diversity

In this part we report more results of unconditional generation which are missing in the main paper for lack of space, showing the diversity of our generated results. From the table we can observe that our method is on par with previous methods. It is worth pointing out that the diversity is hampered to some extent if JSD is too low since the generated geometry can only perfectly mimic existing shapes, and it may also lead to covering issues. Moreover, the high novelty of skexgen is achieved at the cost of generating too many simple CAD sequences, which is shown in N-gram, Embedding Similarity and edit distance shown in the main paper and the qualitative results shown in HNC-CAD.

## 4.4. Details of Showcasing Reconstruction Diversity

As is mentioned in Section 2.2, Minimum Bayes Risk (MBR) decoding is utilized to guide the token selection process. For the results shown in Figure 5 in the main paper, we conduct MBR decoding with top-K sampling combined with MBR size 4 and  $K = 30$ . Particularly, for each CAD model, 4 sequences are preserved in decoding process under the MBR decoding technique and top-30 sampling strategy is used to sample tokens during the decoding process.

## 4.5. Qualitative results on Reconstruction Accuracy

In this part we show more qualitative results on reconstruction accuracy. We filter out easy examples where the number of ground truth primitives are less than 15. The qualitative results are shown in Figure 2 to Figure 14.

## 4.6. Qualitative results on Reconstruction Diversity

In this part, we show more qualitative results on the diversity of the reconstruction. The results are shown in Figure 15 and Figure 17. From the two figures we can observe that our method strikes a balance between reconstruction fidelity and diversity, and the results that are not perfectly accurate also brings about new inspirations to human designers. It is worth noting that Figure 17 is the result under Fusion 360 dataset, which shows that our method is to some extent robust to distribution shift and can reconcile the reconstruction fidelity and diversity under different inputs.

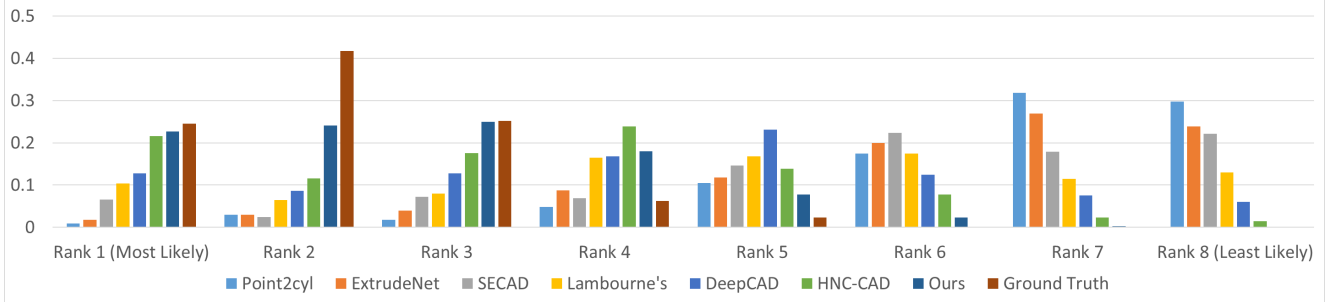


Figure 1. Distribution of votes on which of the reconstructed sequences are more likely to be reused by human designers. 7 human evaluators participate in the reconstructed results of all methods and the ground truth method.

		Tested on DeepCAD Dataset					
ID	Methods	$Acc_{ct}$	$Acc_{cp}$	Med CD	IoU	IR	$\#\Delta P$
A	<b>Our Method</b>	88.55%	82.92%	0.302	0.743	1.48%	2.20
	<i>Removing Diffusion-related Components</i>						
B	– <b>Volume-based Noise Schedule</b>	86.73%	79.47%	0.593	0.642	6.03%	2.47
C	– <b>Multimodal Token-based Diffusion</b>	82.16%	74.23%	0.688	0.627	6.79%	2.59
	<i>Removing Components on Point Cloud Tokenization</i>						
D	– <b>Self-supervised Face Segmentation Pretext Task</b>	81.47%	72.64%	0.832	0.578	9.93%	3.70

Table 2. Ablation Study. – means removing a component from the model exhibited in the previous entry of the table. Median CD is multiplied by  $10^2$ .

#### 4.7. Qualitative results on Unconditional Generation

In this part, we show the qualitative results of unconditional generation. The results are shown in Figure 18.

#### 4.8. Full Results of User Study

In this part we show the complete result of user study. We find 7 participants with design knowledge and asked them to finish the questionnaire on site. The user study contains one question. *The following are CAD sequences originated from the point cloud. Please rank the likeliness of whether you would reuse them.* The full results, covering of the questionnaire, and the first question are shown in Figure 1, Figure 19 and Figure 20 to Figure 24 respectively.

#### 4.9. Ablation Study

In this part we provide a simple ablation study to justify our major design choice. We remove the following designs one by one. (1) *Volume-based noise schedule.* (2) *Multimodal token-based diffusion.* (3) *Self-supervised face segmentation pretext task.* The results are shown in Table 2.

From the table we have the following observations. First, adopting the token-based diffusion strategy greatly boosts the performance of CAD reconstruction accuracy, which is shown between line C and line D in the table, yielding  $\sim 5\%$  performance gain in  $Acc_{ct}$  and  $Acc_{cp}$ . Moreover, the pro-

posed token-based noise-schedule introduces the top-down design strategy into the model, granting it the knowledge of the grammar of CAD construction sequence, as well as linking the CAD geometry with construction sequence. As is shown between line A and line B in the table, the introduction of the noise schedule brings about  $\sim 5\%$  performance gain in **Invalid Rate**, as well as  $\sim 0.3$  performance gain in **Chamfer Distance**. The self-supervised face segmentation pretext task also brings about much performance gain in **Chamfer Distance** and **IoU**, thanks to the design of the pretext task which links the point cloud with the face information in CAD designs.

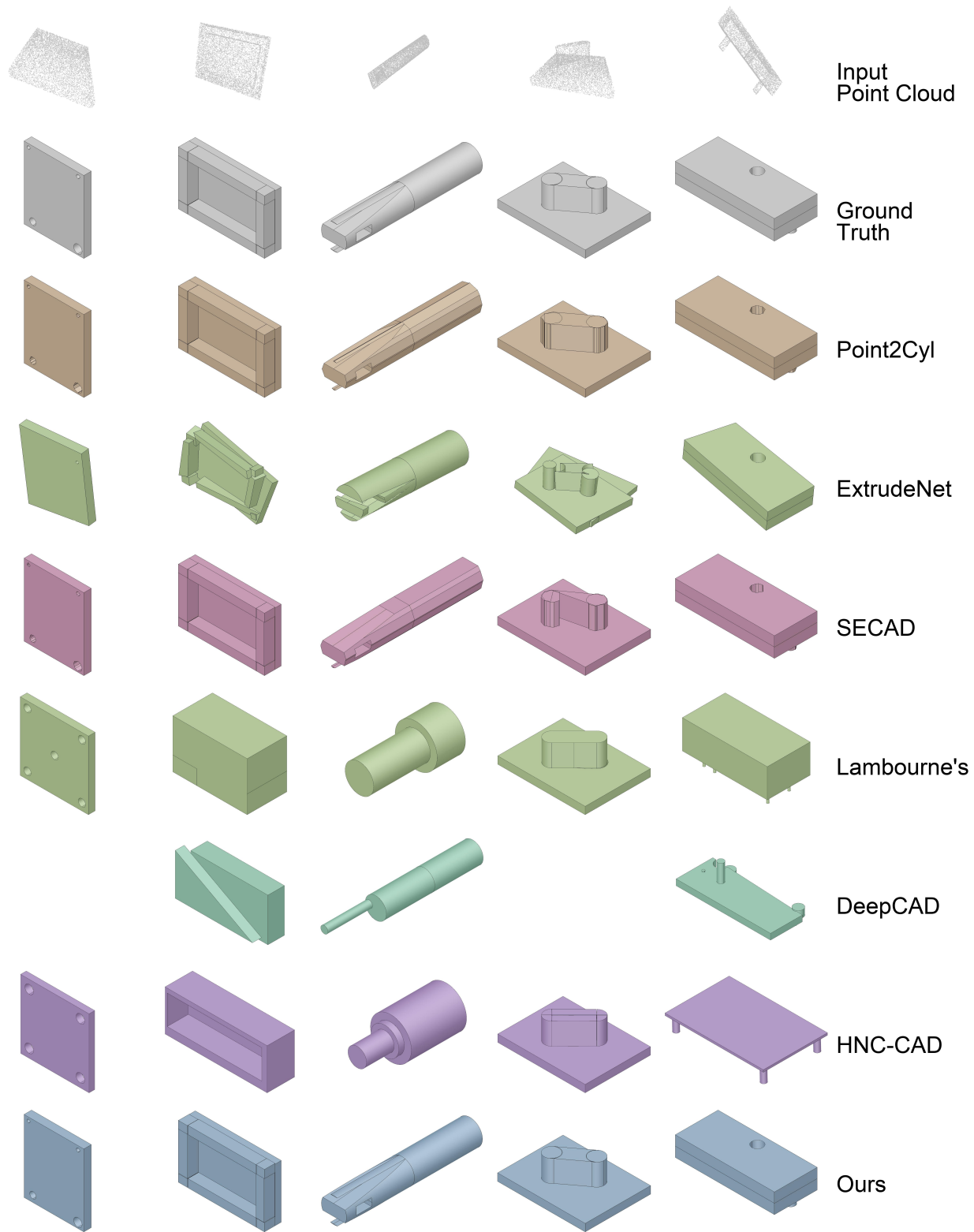


Figure 2. More rendered results of reconstructed CAD sequences. *All images are rendered from the reconstructed CAD sequences.* Results left blank means PythonOCC is not able to render the reconstructed CAD Sequence in a fixed number of time.

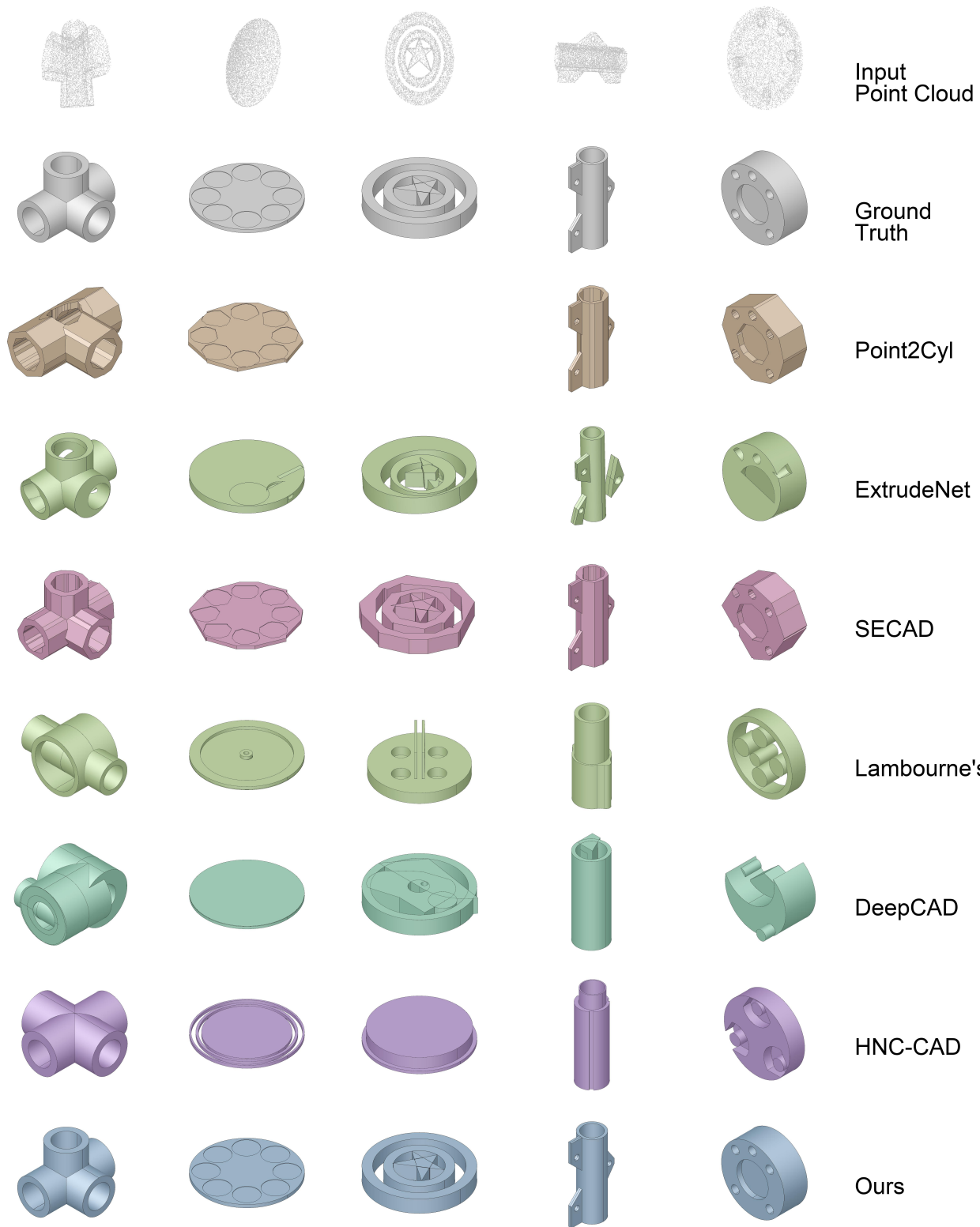


Figure 3. More rendered results of reconstructed CAD sequences. *All images are rendered from the reconstructed CAD sequences.* Results left blank means PythonOCC is not able to render the reconstructed CAD Sequence in a fixed number of time.

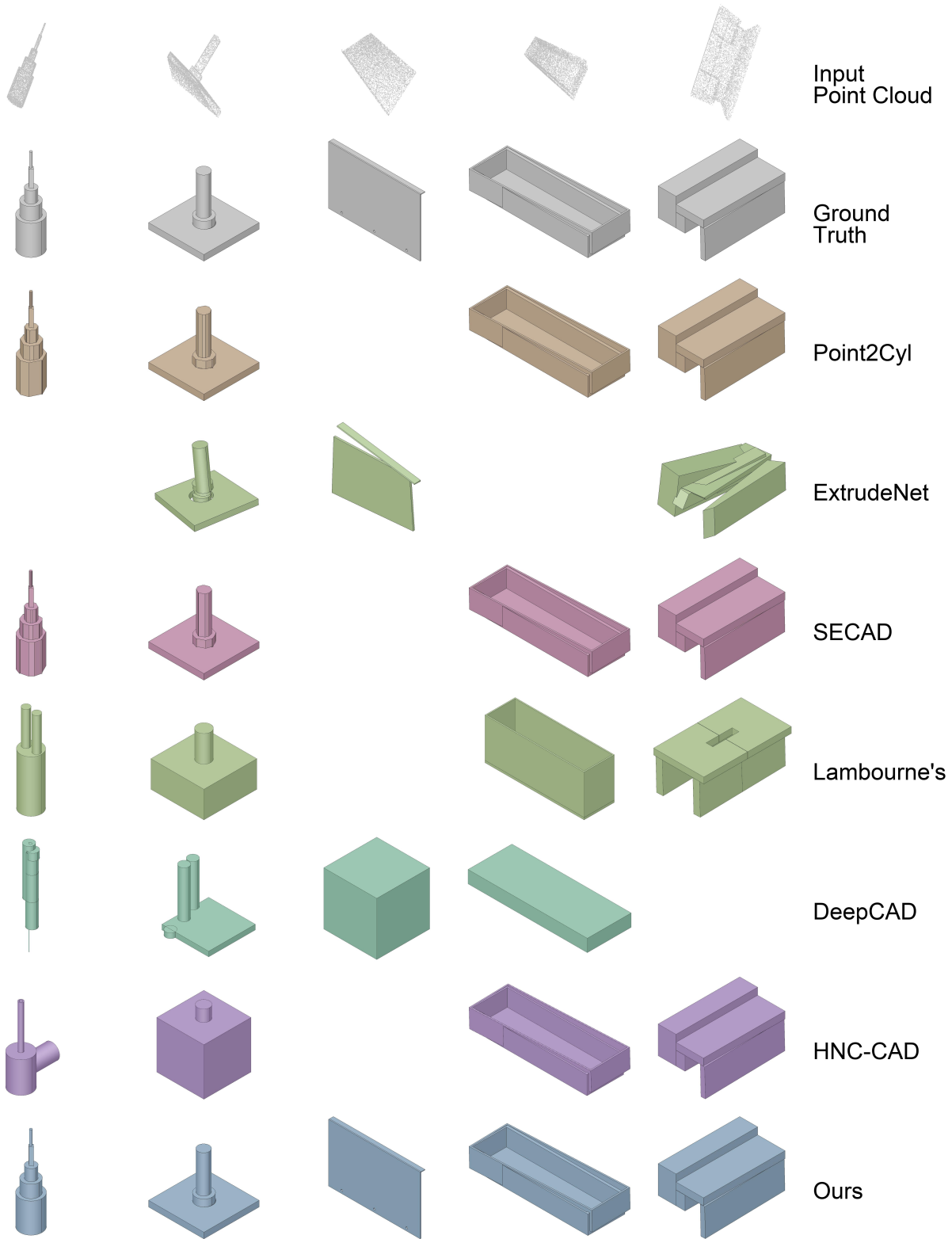


Figure 4. More rendered results of reconstructed CAD sequences. *All images are rendered from the reconstructed CAD sequences.* Results left blank means PythonOCC is not able to render the reconstructed CAD Sequence in a fixed number of time.

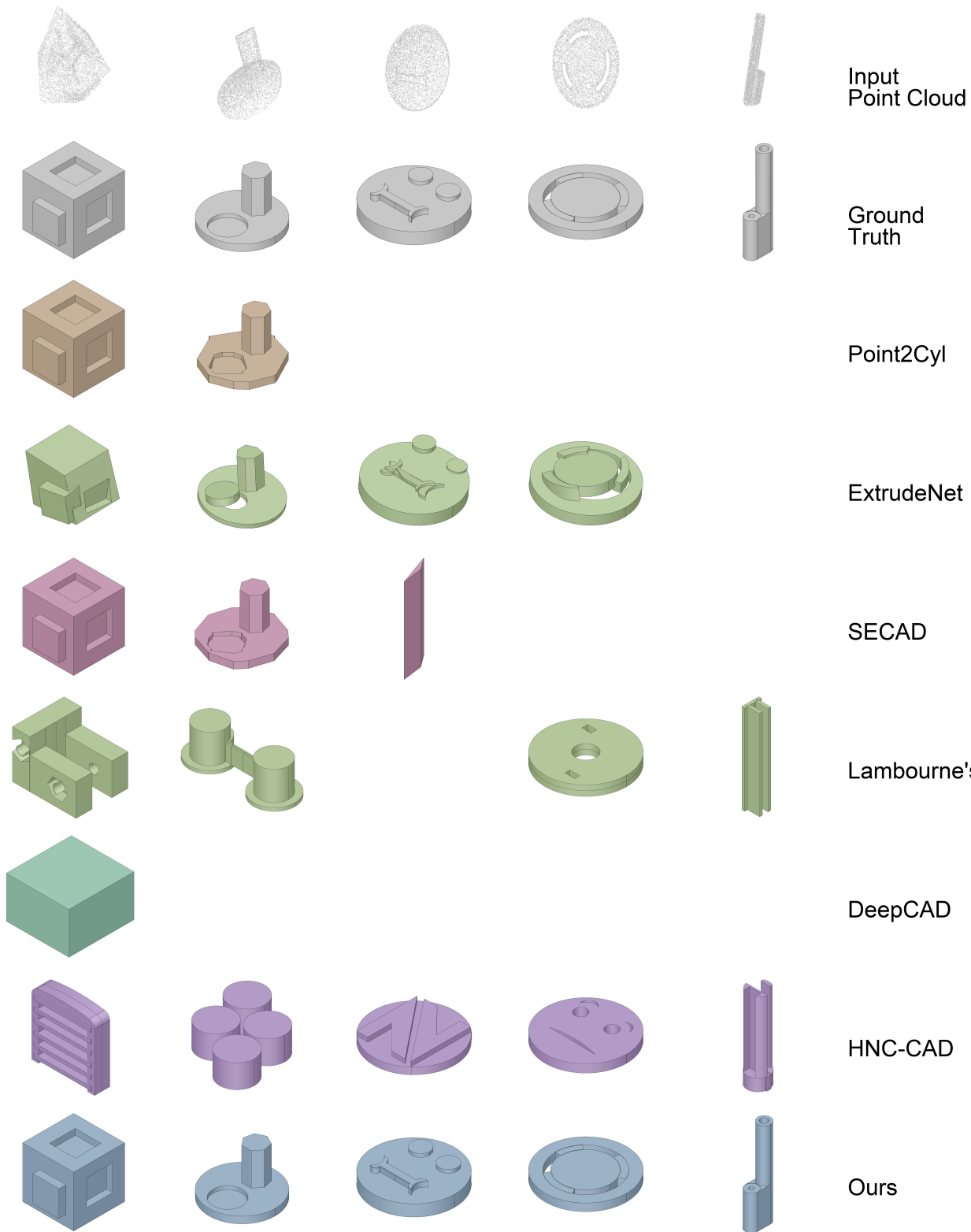


Figure 5. More rendered results of reconstructed CAD sequences. *All images are rendered from the reconstructed CAD sequences.* Results left blank means PythonOCC is not able to render the reconstructed CAD Sequence in a fixed number of time.



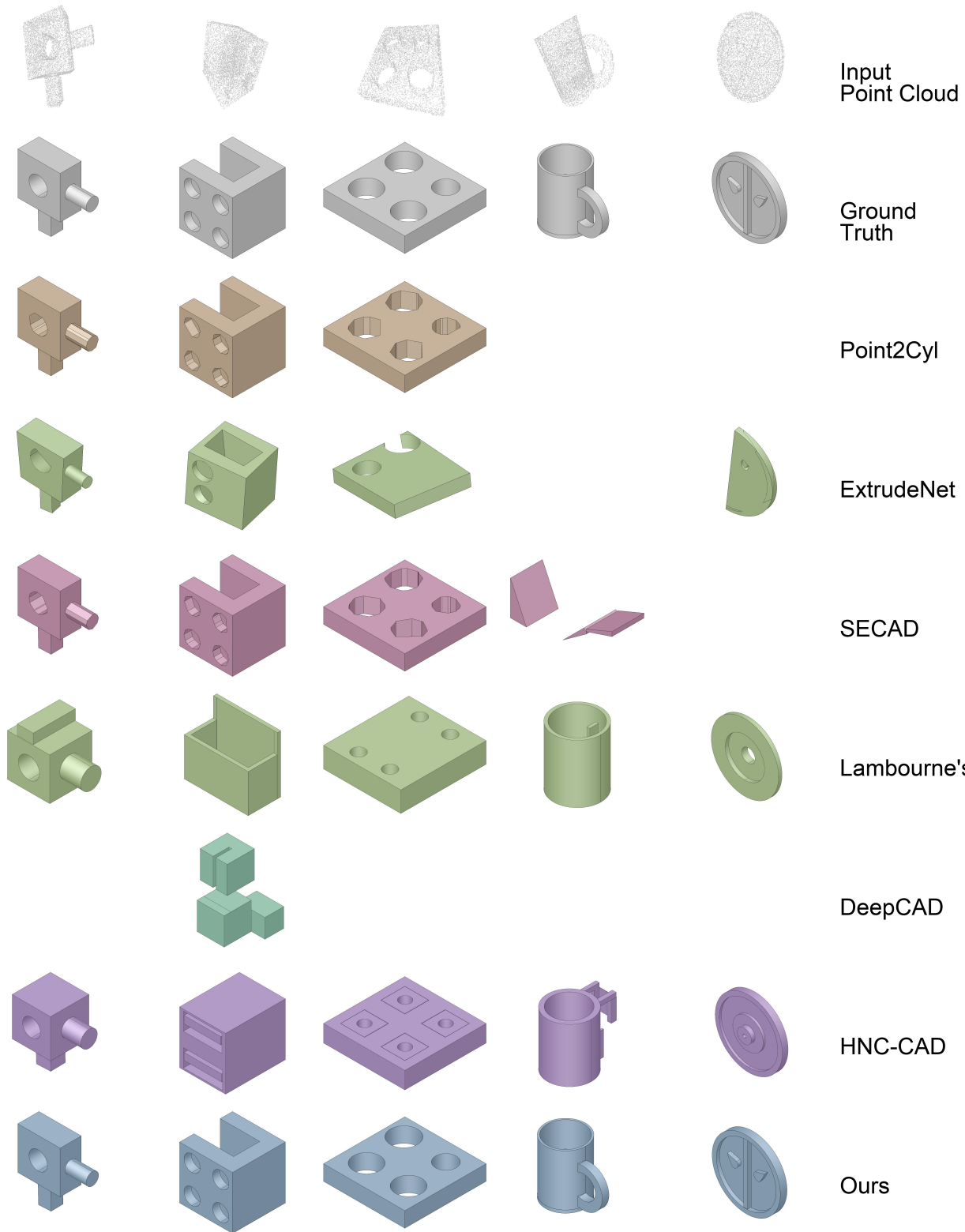


Figure 6. More rendered results of reconstructed CAD sequences. *All images are rendered from the reconstructed CAD sequences.* Results left blank means PythonOCC is not able to render the reconstructed CAD Sequence in a fixed number of time.

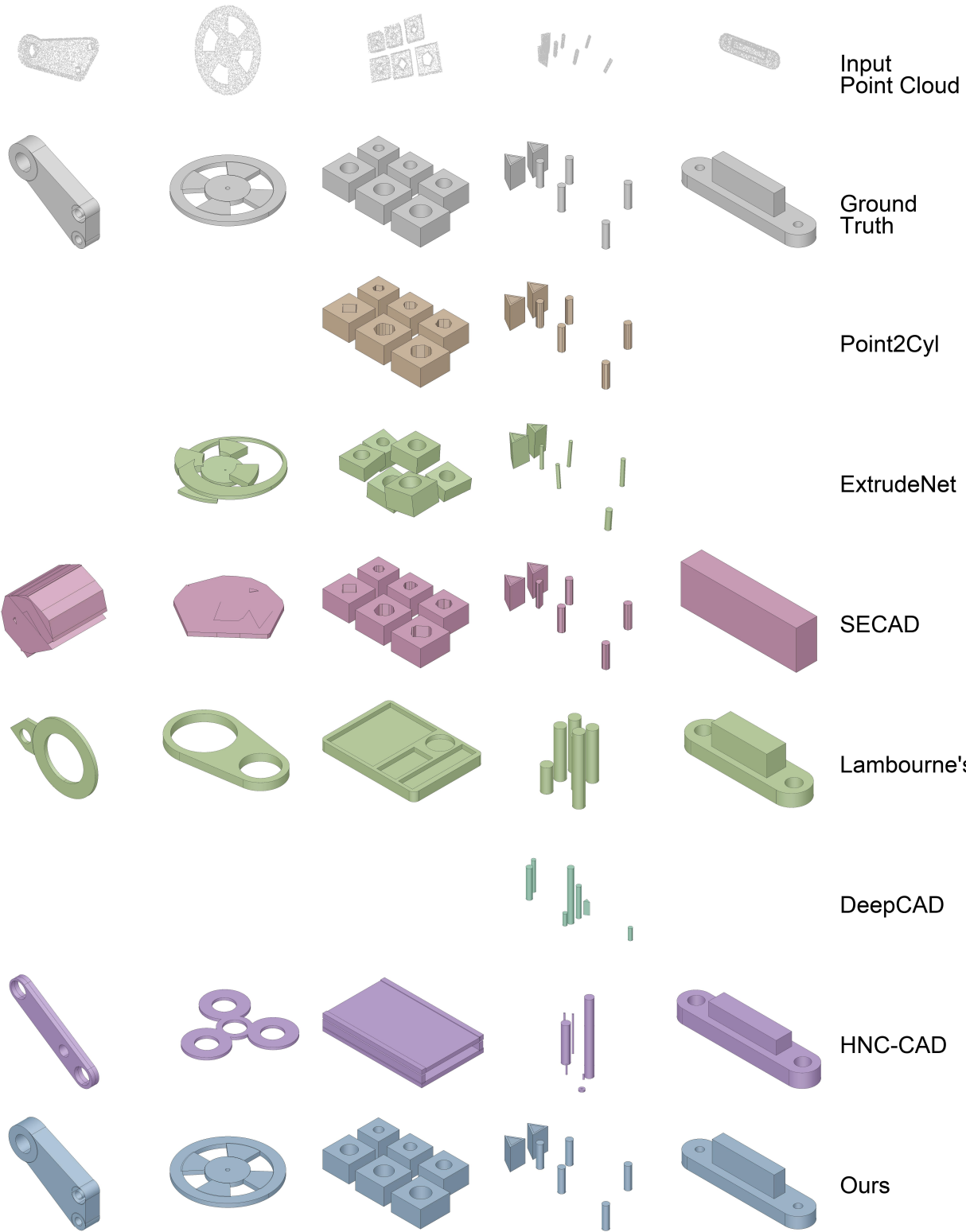


Figure 7. More rendered results of reconstructed CAD sequences. *All images are rendered from the reconstructed CAD sequences.* Results left blank means PythonOCC is not able to render the reconstructed CAD Sequence in a fixed number of time.

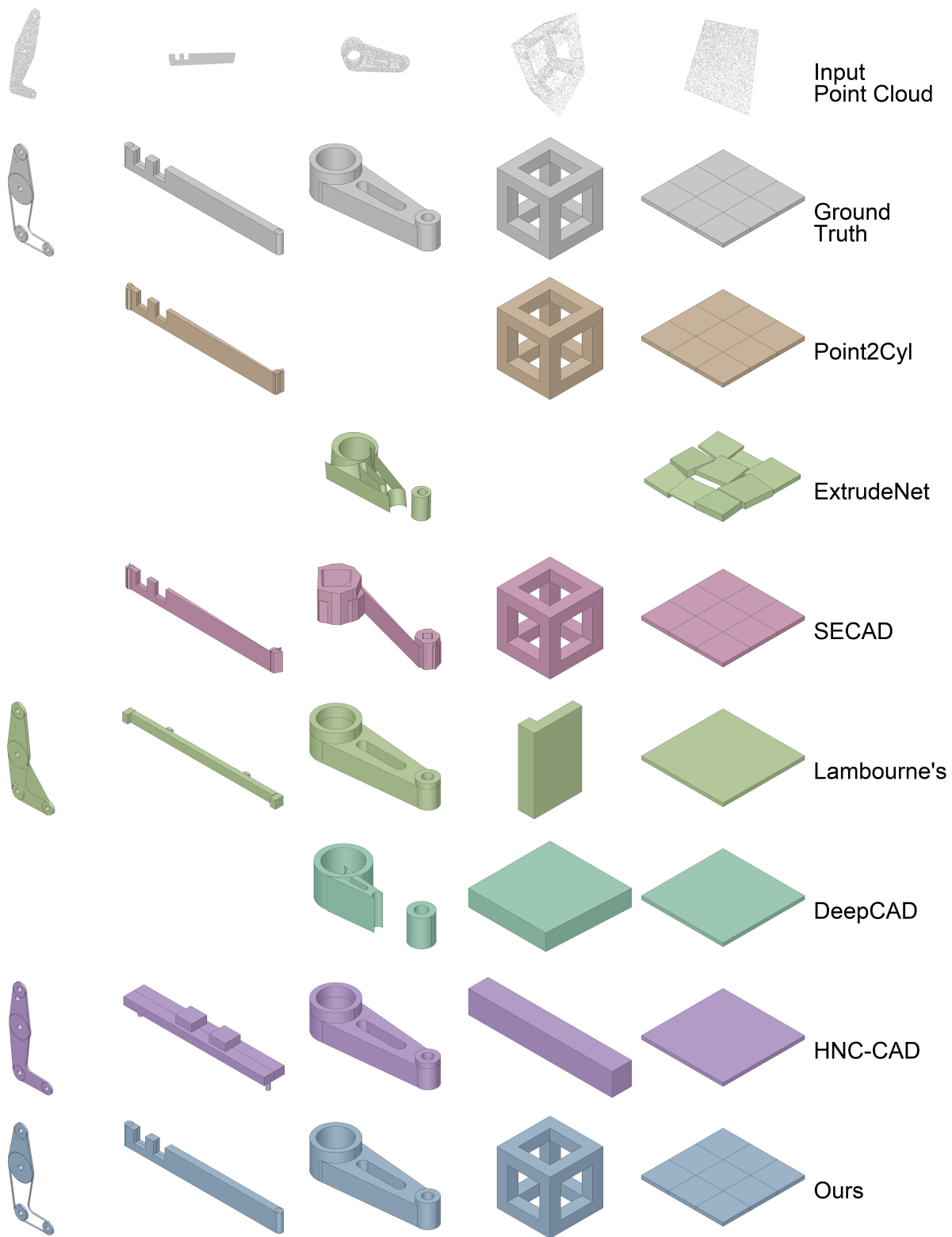


Figure 8. More rendered results of reconstructed CAD sequences. *All images are rendered from the reconstructed CAD sequences.* Results left blank means PythonOCC is not able to render the reconstructed CAD Sequence in a fixed number of time.

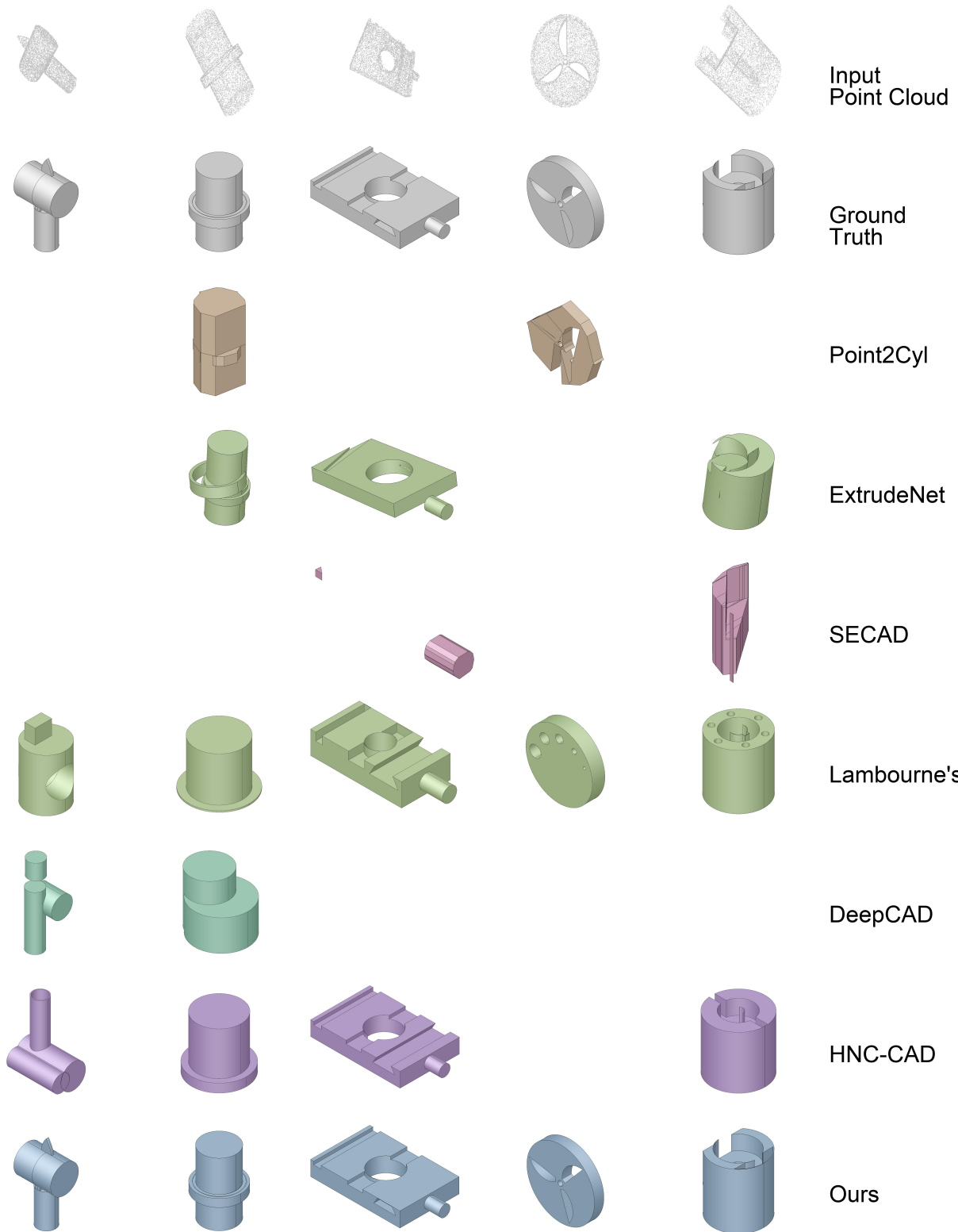


Figure 9. More rendered results of reconstructed CAD sequences. *All images are rendered from the reconstructed CAD sequences.* Results left blank means PythonOCC is not able to render the reconstructed CAD Sequence in a fixed number of time.

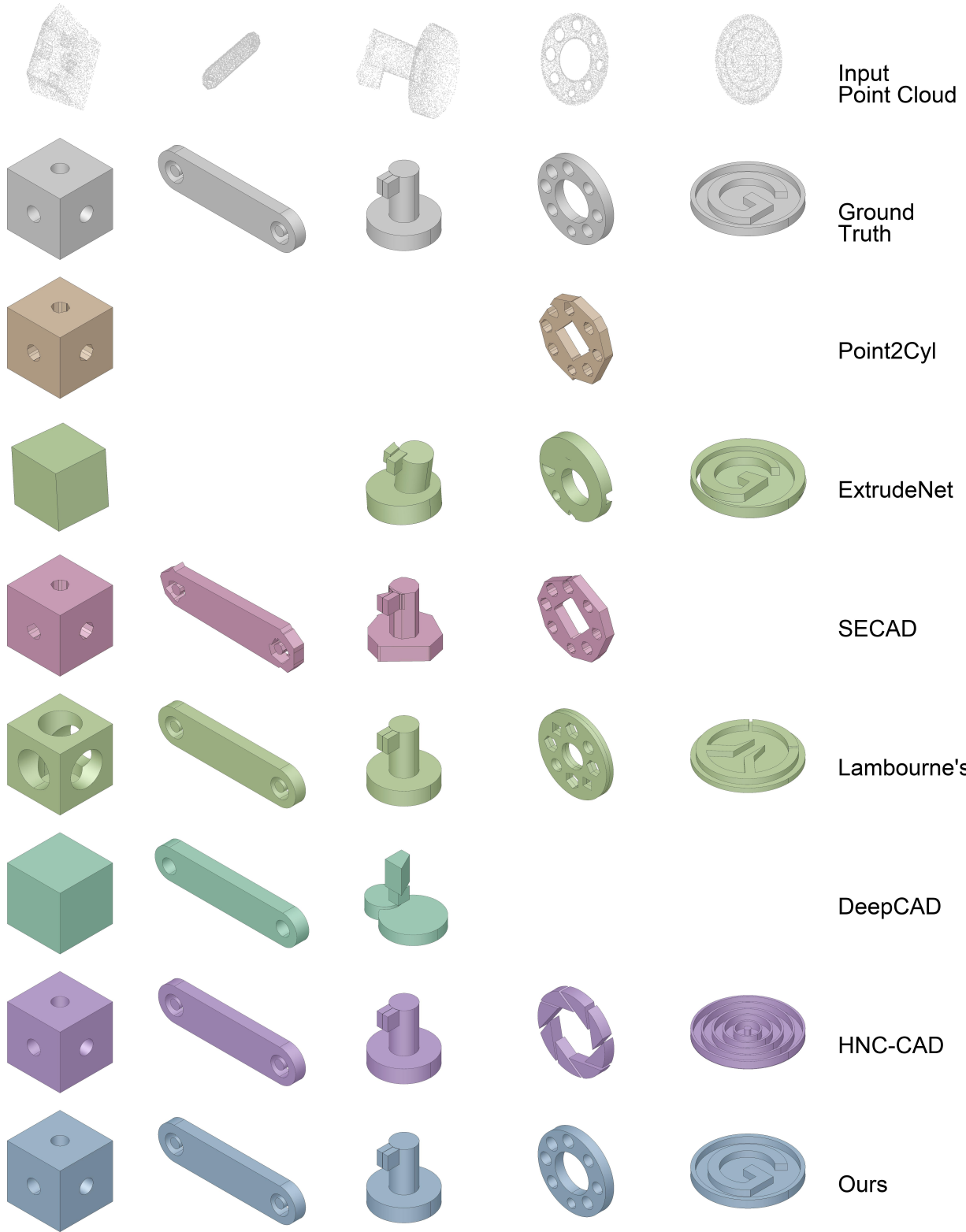


Figure 10. More rendered results of reconstructed CAD sequences. *All images are rendered from the reconstructed CAD sequences.* Results left blank means PythonOCC is not able to render the reconstructed CAD Sequence in a fixed number of time.

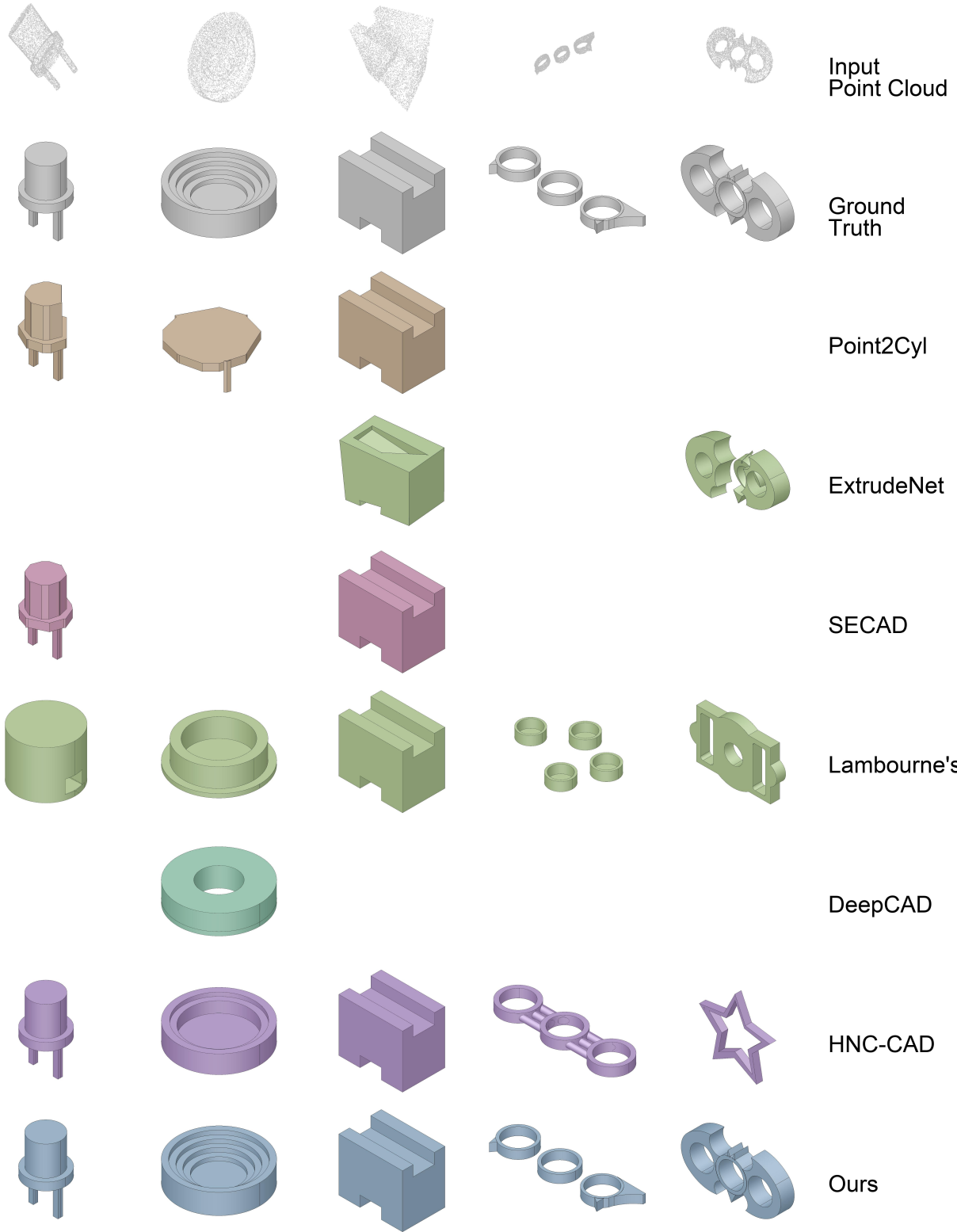


Figure 11. More rendered results of reconstructed CAD sequences. *All images are rendered from the reconstructed CAD sequences.* Results left blank means PythonOCC is not able to render the reconstructed CAD Sequence in a fixed number of time.

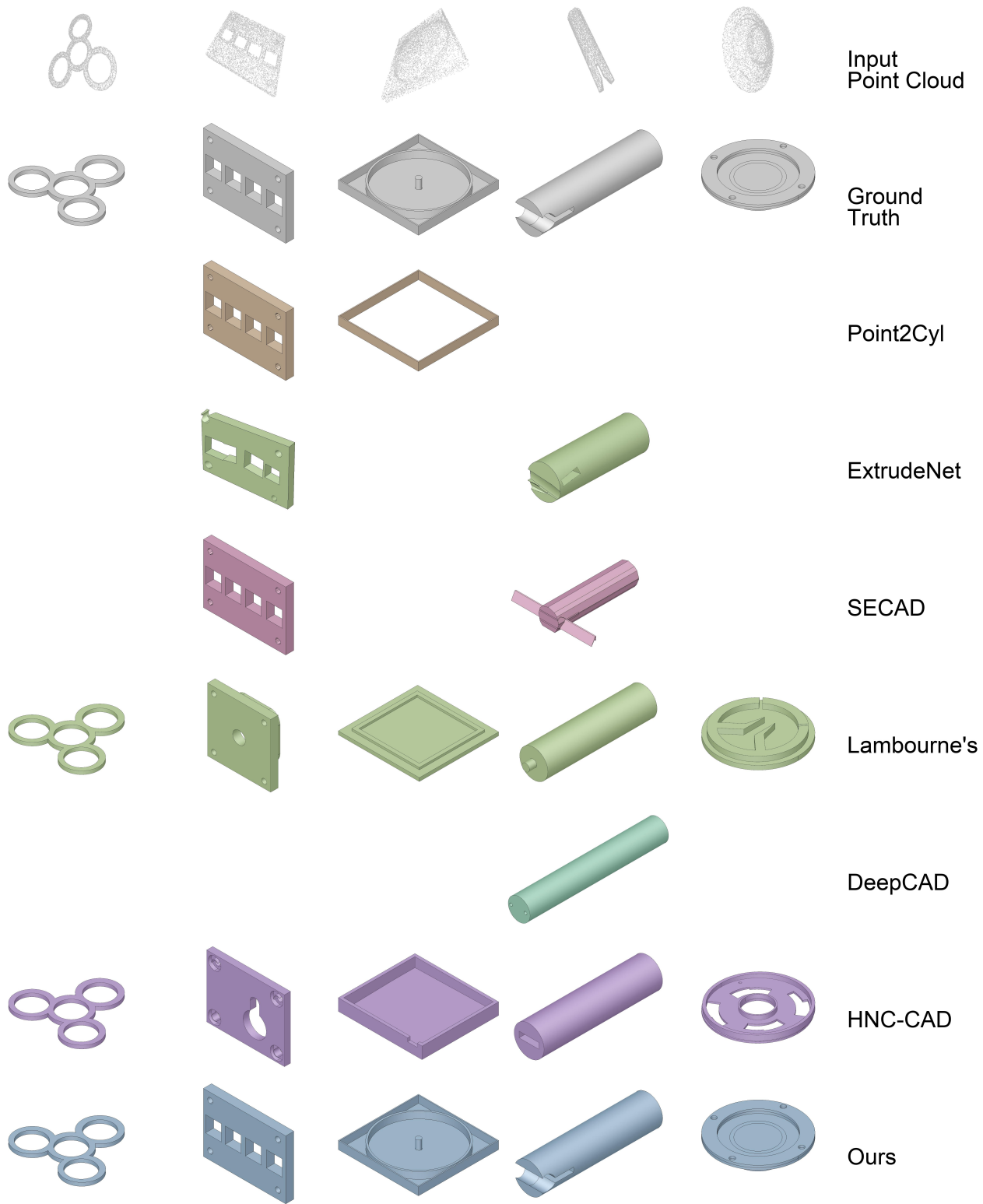


Figure 12. More rendered results of reconstructed CAD sequences. *All images are rendered from the reconstructed CAD sequences.* Results left blank means PythonOCC is not able to render the reconstructed CAD Sequence in a fixed number of time.

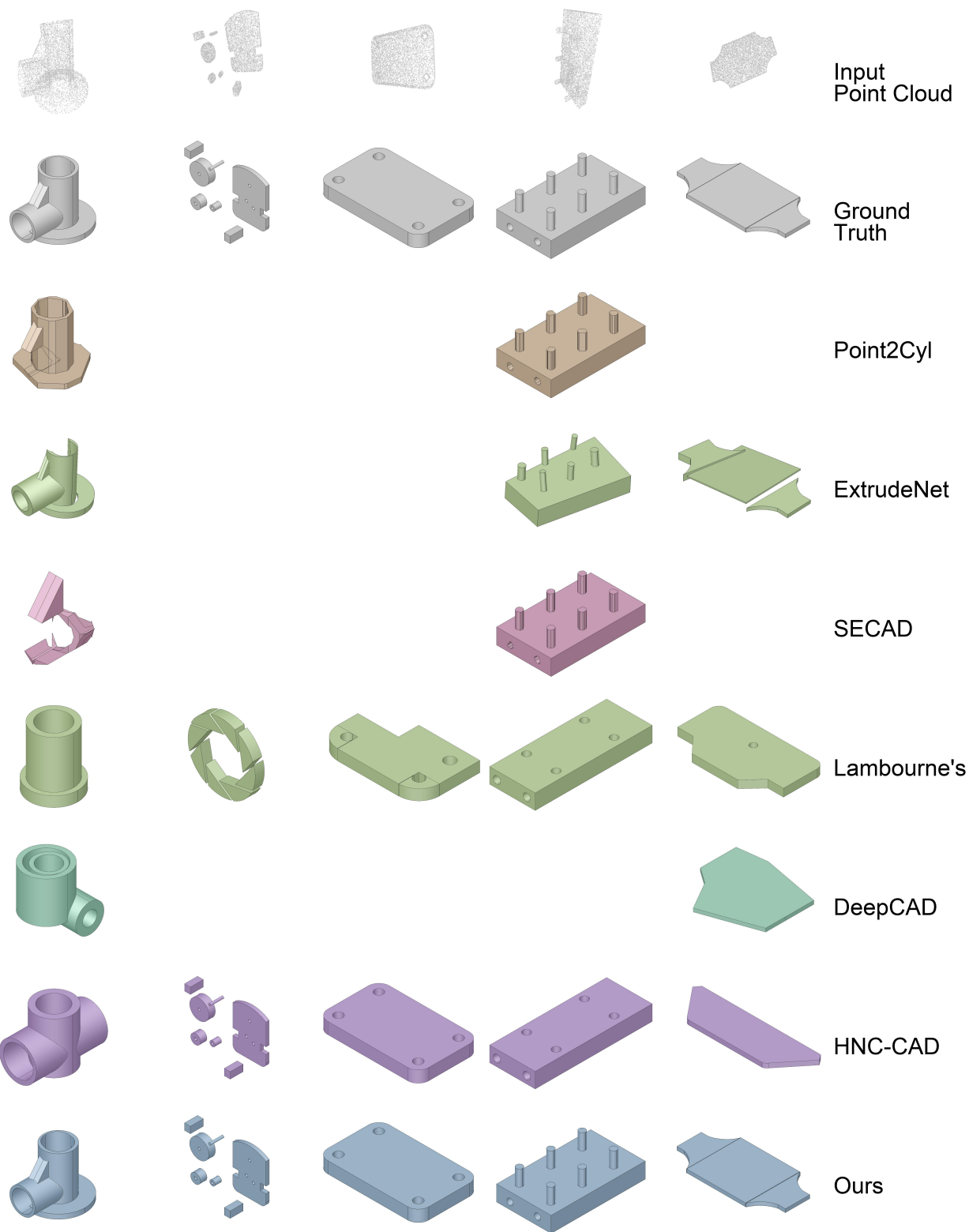


Figure 13. More rendered results of reconstructed CAD sequences. *All images are rendered from the reconstructed CAD sequences.* Results left blank means PythonOCC is not able to render the reconstructed CAD Sequence in a fixed number of time.



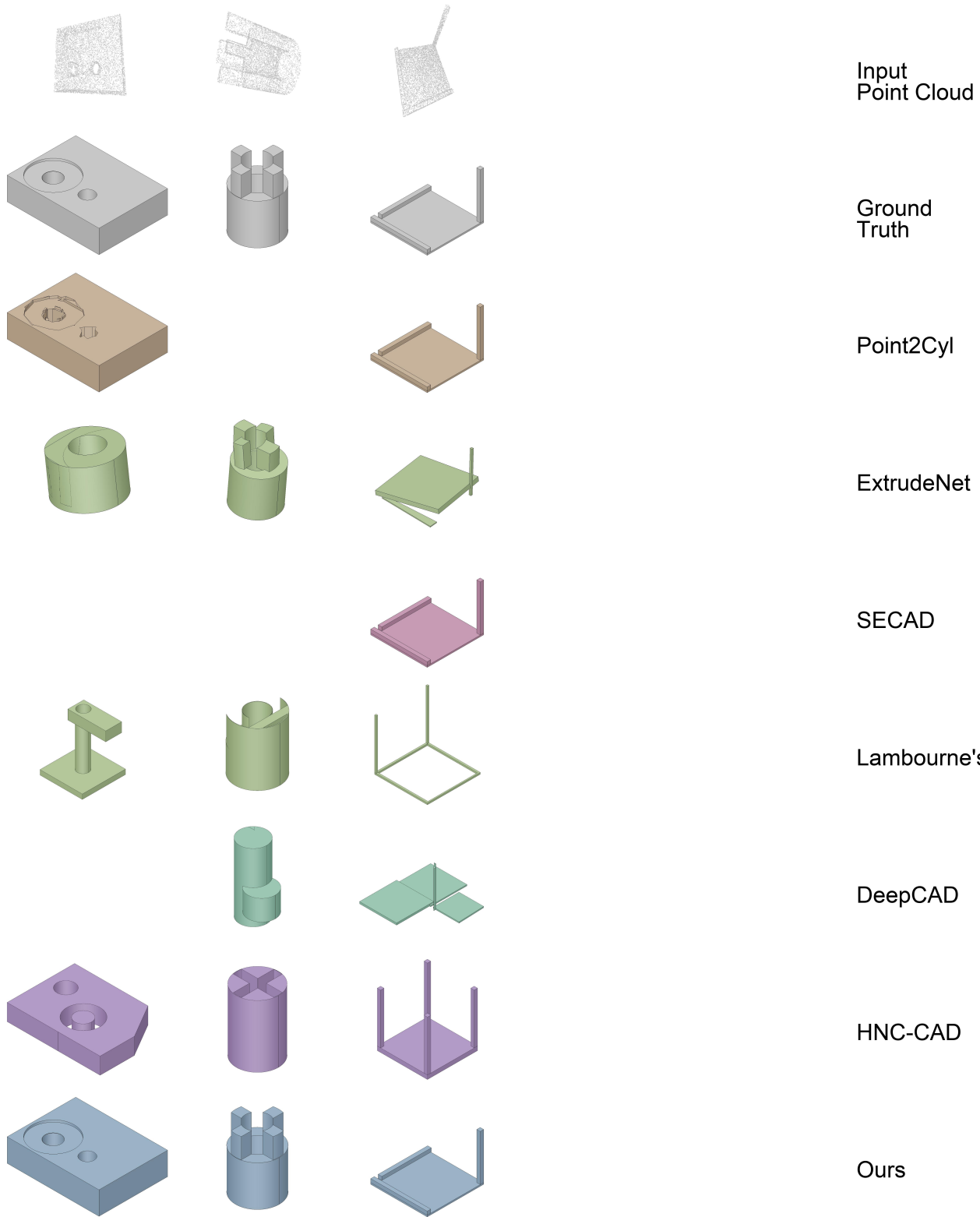


Figure 14. More rendered results of reconstructed CAD sequences. *All images are rendered from the reconstructed CAD sequences.* Results left blank means PythonOCC is not able to render the reconstructed CAD Sequence in a fixed number of time.

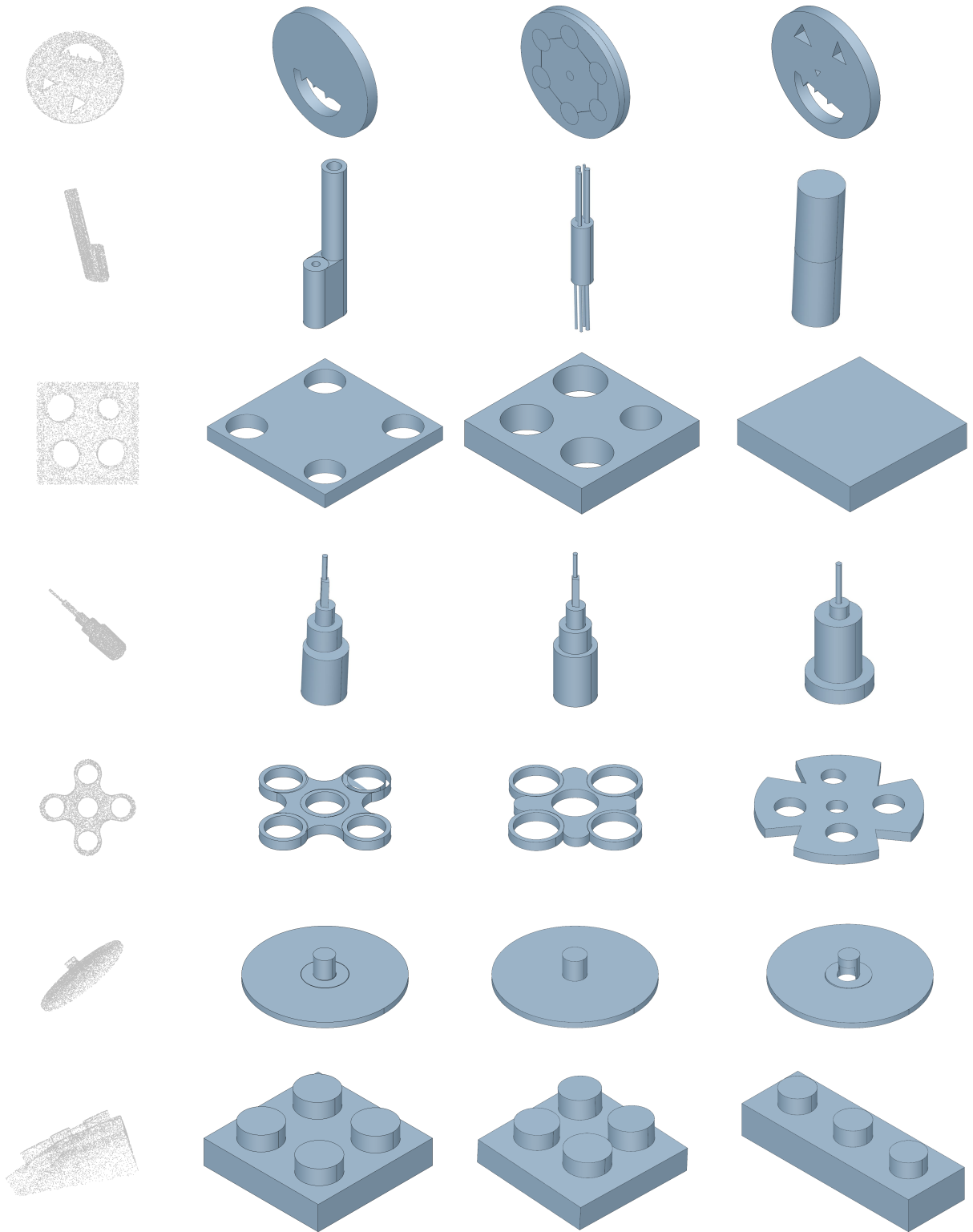


Figure 15. More rendered results of reconstruction diversity.

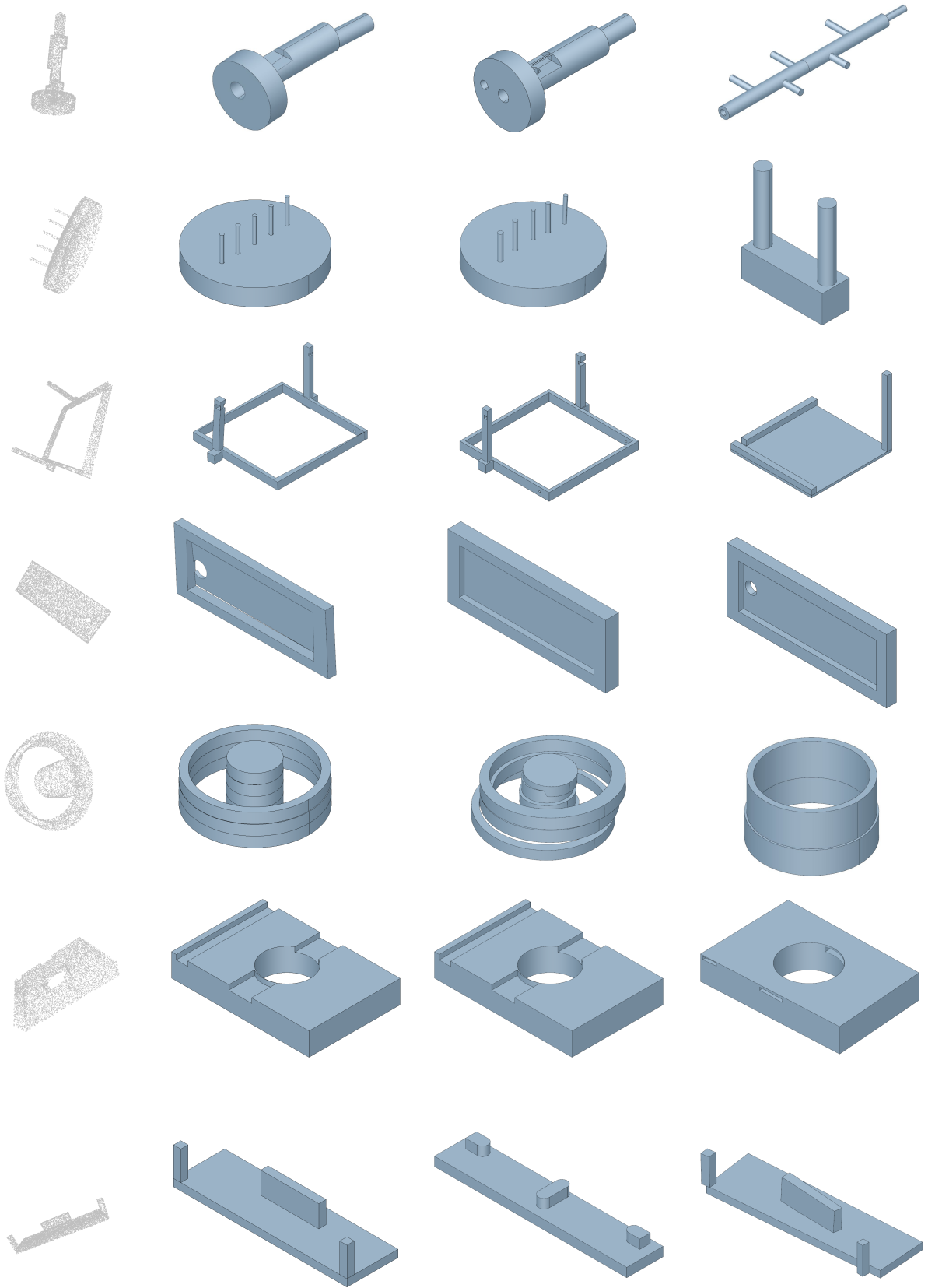


Figure 16. More rendered results of reconstruction diversity.

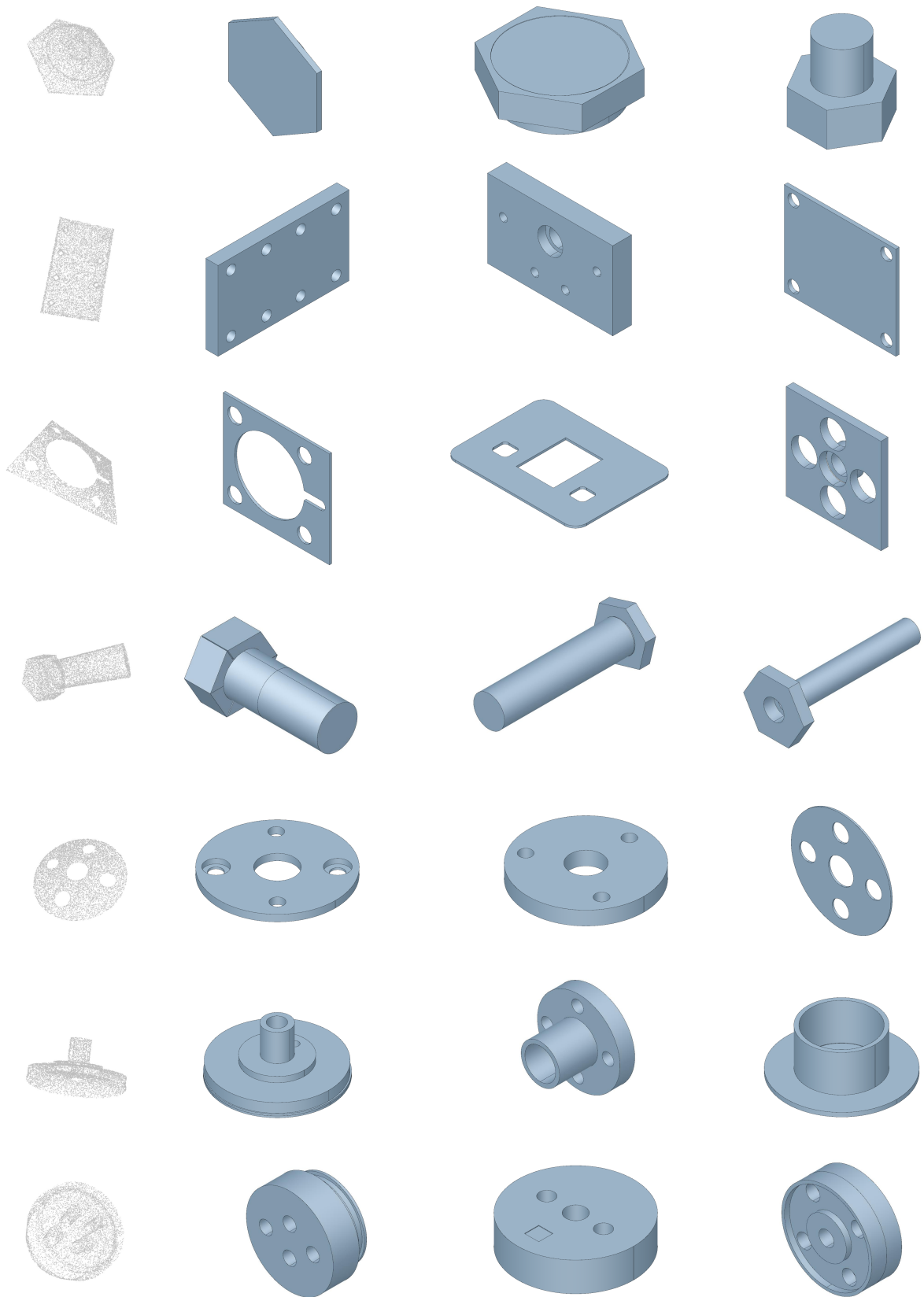


Figure 17. Rendered results of reconstruction diversity under Fusion 360 dataset. The result shows that our method is to some extent robust to distribution shift.

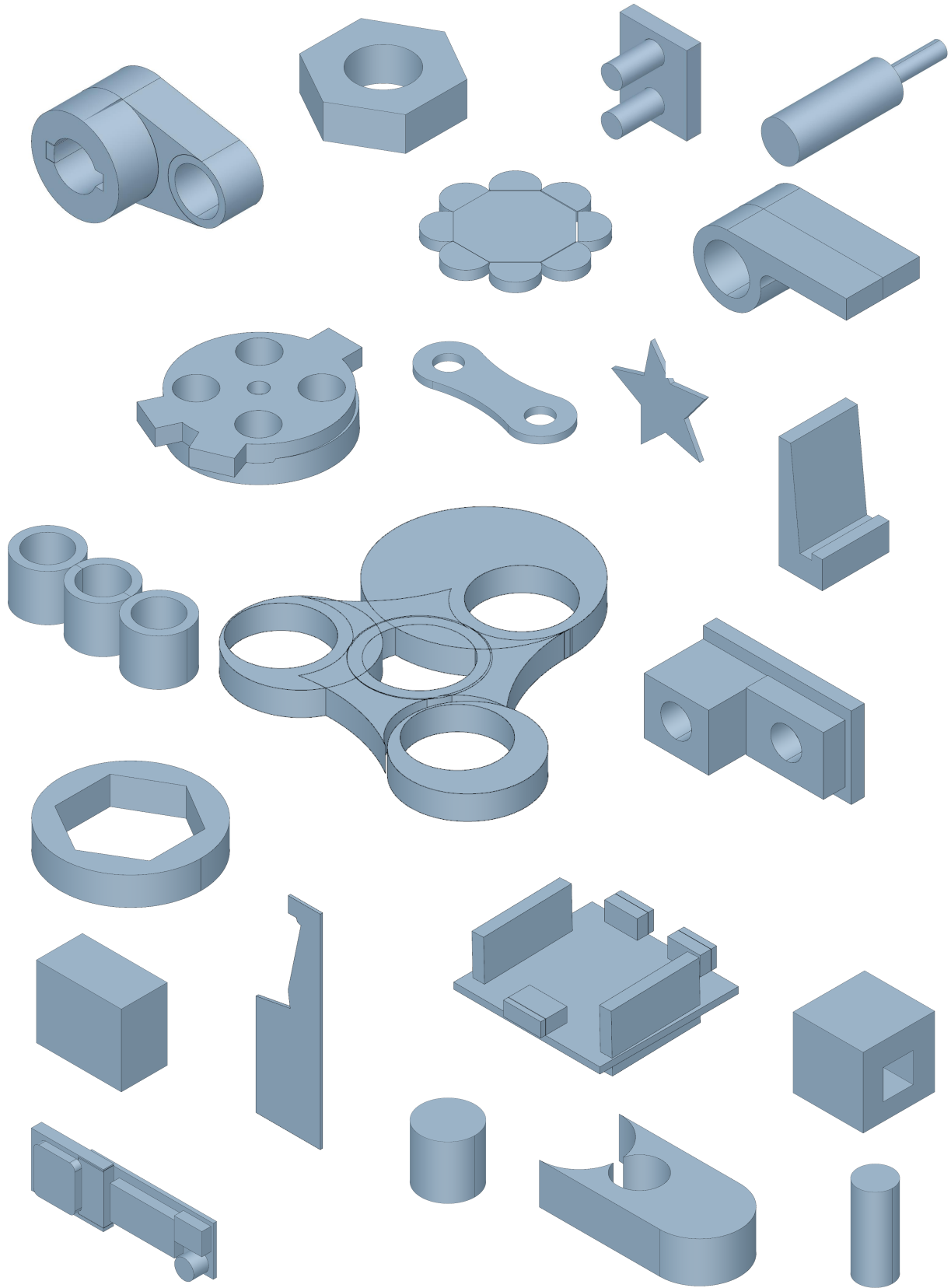


Figure 18. Rendered results of unconditional generation.

## User Study on the Reusability of Reconstructed CAD Construction Sequence under Different Methods

You are invited to answer this questionnaire. Your answer is of great importance to assess the quality of different reconstruction methods.

Below are the reconstructed CAD construction sequences under 8 different methods. Would you please kindly rank the reconstructed results on how much you would likely to reuse the reconstructed CAD construction sequences.

For the sequence you are most likely to reuse, please rank 1. For the sequence you are least likely to reuse, please rank 8.

Note: Each CAD sequence are in CSG format which is encoded as the following picture shows.

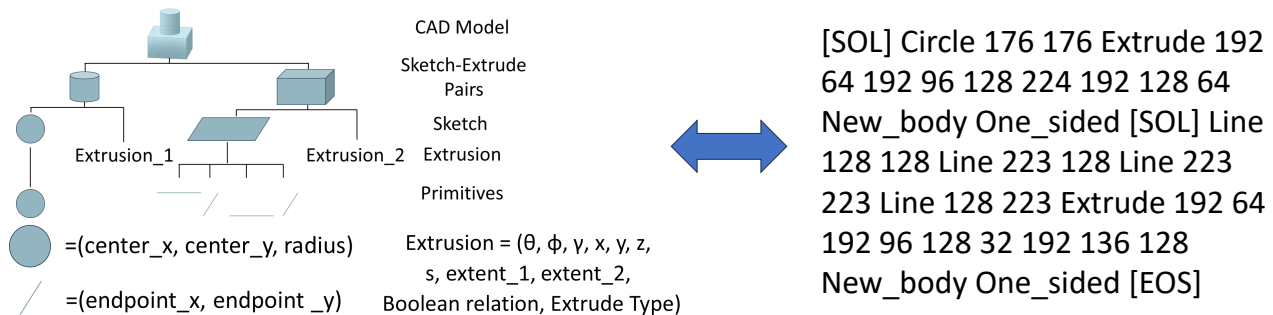


Figure 19. The questionnaire cover of the user study. Each participant is told the target of the task, the ranking method and the grammar of the CAD sequence.

Input  
Point  
Cloud

Converted CAD Sequences

Rendered  
Geometry

Rankings



Model 1  
Page  
1 of 5

[SOL] Line 224 129 Line 215 155 Line 205 169 Line 178 175  
Line 176 175 Line 129 130 Line 128 129 Line 128 128 Line  
136 102 Line 147 89 Line 176 79 Line 178 80 Line 205 91 Line  
226 128 Line 225 128 [SOL] Line 224 129 Line 223 129 Line  
208 162 Line 178 173 Line 176 176 Line 176 174 Line 145  
162 Line 142 160 Line 131 130 Line 141 98 Line 177 82 Line  
177 83 Line 209 96 Line 211 97 Line 221 128 Extrude 192 128  
192 128 32 128 192 147 128 New\_body One\_sided [SEP]  
[SOL] Line 221 89 Line 222 95 Line 217 142 Line 212 146 Line  
206 149 Line 136 123 Line 178 68 Line 220 88 Line 134 140  
Line 129 127 Line 123 107 Line 121 106 Line 232 207 Line  
213 203 Line 134 140 Extrude 192 128 192 128 43 164 56  
147 128 Join One\_sided [SEP] [SOL] Line 224 131 Line 205  
169 Line 176 175 Line 176 176 Line 150 166 Line 128 129  
Line 128 128 Line 130 127 Line 138 99 Line 148 91 Line 175  
80 Line 176 79 Line 203 88 Line 223 127 Line 225 127 [SOL]  
Line 217 129 Line 214 145 Line 193 166 Line 178 166 Line  
161 166 Line 139 144 Line 139 130 Line 136 129 Line 136  
126 Line 140 115 Line 176 88 Line 178 89 Line 192 94 Line  
213 113 Line 216 128 Extrude 192 128 192 128 96 128 65  
147 128 Join One\_sided [SEP] [SOL] Line 129 128 Line 130  
126 Line 175 101 Line 215 157 Line 146 186 Line 141 182  
Line 137 177 Line 223 163 Line 224 162 Line 209 254 Line  
217 177 Line 128 128 Extrude 192 128 192 128 157 143 56  
147 128 Join One\_sided [SEP] [SOL] Line 133 33 Line 167 44  
Line 171 115 Line 156 126 Line 148 131 Line 124 130 Line  
113 125 Line 101 118 Line 95 111 Line 90 103 Line 106 44  
Line 145 128 Line 129 129 Line 68 110 Line 26 73 Line 249 71  
Line 208 110 Line 146 127 Extrude 192 128 192 128 123 220  
60 147 128 Join One\_sided [SEP] [SOL] Line 129 128 Line 135  
117 Line 219 118 Line 224 129 Line 225 132 Line 228 141  
Line 124 141 Line 128 135 Line 192 142 Line 193 142 Line  
191 159 Line 158 158 Line 159 144 Line 167 135 Line 172  
132 Line 180 131 Line 183 133 Line 128 128 Extrude 192 128  
192 128 44 90 168 147 128 Join One\_sided [SEP] [SOL] Line  
129 128 Line 157 106 Line 192 105 Line 225 128 Line 194  
141 Line 196 143 Line 198 146 Line 202 152 Line 150 151  
Line 151 149 Line 155 146 Line 156 140 Line 159 139 Line  
178 132 Line 193 140 Line 128 128 Extrude 192 128 192 128  
57 83 141 114 128 Cut One\_sided [SEP] [EOS]



Please write  
your rankings  
(1-8) in the box.

Figure 20. An example model in our questionnaire. (1 of 5)

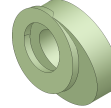
Input  
Point  
Cloud

### Converted CAD Sequences

Rendered  
Geometry

Rankings

[SOL] Circle 178 129 450 [SOL] Circle 176 128 25  
Extrude 190 67 195 101 126 129 64 138 130  
New\_body One\_sided [SEP] [SOL] Circle 176 128 48  
[SOL] Circle 179 131 24 Extrude 194 67 195 98 112  
126 58 130 131 Join One\_sided [SEP] [EOS]



[SOL] Circle 176 128 48 [SOL] Circle 176 128 46 Extrude  
192 128 192 128 32 128 192 147 128 New\_body  
One\_sided [SEP] [SOL] Line 221 89 Arc 223 93 4  
Counterclockwise Line 134 140 Arc 128 128 4  
Counterclockwise Extrude 192 128 192 128 43 164 56  
147 128 Join One\_sided [SEP] [SOL] Circle 176 128 48  
[SOL] Circle 176 128 39 Extrude 192 128 192 128 96  
128 65 147 128 Join One\_sided [SEP] [SOL] Arc 130 124  
4 Counterclockwise Line 223 163 Arc 217 176 4  
Clockwise Line 128 128 Extrude 192 128 192 128 157  
143 56 147 128 Join One\_sided [SEP] [SOL] Line 133 33  
Arc 139 33 5 Counterclockwise Line 145 128 Arc 128  
128 5 Counterclockwise Extrude 192 128 192 128 123  
220 60 147 128 Join One\_sided [SEP] [SOL] Arc 223 128  
93 Counterclockwise Line 192 142 Arc 159 142 93  
Clockwise Line 128 128 Extrude 192 128 192 128 44 90  
168 147 128 Join One\_sided [SEP] [SOL] Arc 223 128 81  
Counterclockwise Line 194 141 Arc 157 141 67  
Clockwise Line 128 128 Extrude 192 128 192 128 57 83  
141 114 128 Cut One\_sided [SEP] [EOS]



[SOL] Circle 176 128 48 [SOL] Arc 170 92 51  
Counterclockwise Line 170 121 Arc 169 122 5  
Counterclockwise Line 139 122 [SOL] Line 169 134  
Arc 170 135 5 Counterclockwise Line 170 164 Arc  
139 134 51 Counterclockwise [SOL] Circle 176 128 3  
[SOL] Arc 212 122 51 Counterclockwise Line 182 122  
Arc 181 121 5 Counterclockwise Line 181 92 [SOL]  
Arc 182 134 5 Counterclockwise Line 212 134 Arc  
181 164 51 Counterclockwise Line 181 135 Extrude  
192 64 192 32 128 128 192 116 128 New\_body  
One\_sided [SEP] [EOS]



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Please write  
your rankings  
(1-8) in the box.

Figure 21. An example model in our questionnaire. (2 of 5)



Input  
Point  
Cloud

### Converted CAD Sequences

Rendered  
Geometry

Rankings

[SOL] Circle 176 128 48 [SOL] Circle 176 128 41 [SOL] Circle 144 159 3 Extrude 192 64 192 32 128 128 192 148 128 New\_body One\_sided [SEP] [SOL] Line 156 142 Line 156 55 Line 183 196 Line 156 176 Line 170 222 Arc 146 223 6 Counterclockwise Line 128 128 Extrude 192 64 192 114 128 164 46 148 128 Join One\_sided [SEP] [SOL] Line 156 142 Line 156 55 Line 183 196 Line 156 176 Line 170 222 Arc 146 223 6 Counterclockwise Line 128 128 Extrude 192 64 192 114 128 164 46 148 128 Join One\_sided [SEP] [SOL] Arc 128 114 6 Counterclockwise Line 154 122 Line 143 107 Line 223 122 Line 173 122 Line 181 138 Line 128 128 Extrude 192 64 192 46 128 133 82 148 128 Join One\_sided [SEP] [EOS]



[SOL] Circle 176 128 48 [SOL] Circle 176 128 46 Extrude 192 128 192 128 32 128 192 147 128 New\_body One\_sided [SEP] [SOL] Line 221 89 Arc 223 93 4 Counterclockwise Line 134 140 Arc 128 128 4 Counterclockwise Extrude 192 128 192 128 43 164 56 147 128 Join One\_sided [SEP] [SOL] Circle 176 128 48 [SOL] Circle 176 128 39 Extrude 192 128 192 128 96 128 65 147 128 Join One\_sided [SEP] [SOL] Arc 130 124 4 Counterclockwise Line 223 163 Arc 217 176 4 Clockwise Line 128 128 Extrude 192 128 192 128 157 143 56 147 128 Join One\_sided [SEP] [SOL] Line 133 33 Arc 139 33 5 Counterclockwise Line 145 128 Arc 128 128 5 Counterclockwise Extrude 192 128 192 128 123 220 60 147 128 Join One\_sided [SEP] [SOL] Arc 223 128 93 Counterclockwise Line 192 142 Arc 159 142 93 Clockwise Line 128 128 Extrude 192 128 192 128 44 90 168 147 128 Join One\_sided [SEP] [SOL] Arc 223 128 81 Counterclockwise Line 194 141 Arc 157 141 67 Clockwise Line 128 128 Extrude 192 128 192 128 57 83 141 114 128 Cut One\_sided [SEP] [EOS]



Model 1  
Page  
3 of 5

Please write  
your rankings  
(1-8) in the box.

Figure 22. An example model in our questionnaire. (3 of 5)



Input	Converted CAD Sequences	Rendered	Rankings
Point Cloud	<p>[SOL] Line 224 129 Line 224 131 Line 217 156 Line 206 166  Line 177 176 Line 136 156 Line 129 130 Line 128 130 Line  129 127 Line 150 90 Line 175 79 Line 177 79 Line 179 80  Line 203 88 Line 225 126 [SOL] Line 223 129 Line 221 130  Line 210 158 Line 177 176 Line 143 160 Line 131 131 Line  132 130 Line 132 128 Line 147 96 Line 177 81 Line 177 82  Line 179 84 Line 206 95 Line 211 97 Line 224 126 Extrude  192 128 192 128 32 128 192 147 128 New_body  One_sided [SEP] [SOL] Line 221 89 Line 220 90 Line 224 95  Line 214 142 Line 211 147 Line 209 150 Line 139 123 Line  178 67 Line 134 140 Line 130 128 Line 123 110 Line 122  106 Line 232 208 Line 212 202 Line 136 142 Extrude 192  128 192 128 43 164 56 147 128 Join One_sided [SEP] [SOL]  Line 216 155 Line 206 166 Line 178 175 Line 177 176 Line  149 169 Line 137 156 Line 128 130 Line 129 128 Line 139  102 Line 148 91 Line 175 79 Line 176 82 Line 177 80 Line  223 126 Line 223 128 [SOL] Line 215 131 Line 214 142 Line  193 163 Line 176 169 Line 175 167 Line 162 163 Line 139  144 Line 138 130 Line 137 126 Line 142 114 Line 160 93  Line 174 88 Line 175 90 Line 214 115 Line 214 128 Extrude  192 128 192 128 96 128 65 147 128 Join One_sided [SEP]  [SOL] Line 129 127 Line 130 126 Line 174 100 Line 214 157  Line 143 184 Line 141 179 Line 138 179 Line 223 163 Line  224 163 Line 208 253 Line 218 178 Line 128 128 Extrude  192 128 192 128 157 143 56 147 128 Join One_sided [SEP]  [SOL] Line 133 33 Line 135 35 Line 176 52 Line 171 116  Line 172 117 Line 161 125 Line 115 127 Line 115 126 Line  102 117 Line 97 109 Line 105 44 Line 145 128 Line 145  129 Line 127 129 Line 66 109 Line 25 74 Line 250 74 Line  209 110 Extrude 192 128 192 128 123 220 60 147 128 Join  One_sided [SEP] [SOL] Line 130 128 Line 135 119 Line 218  117 Line 225 128 Line 225 135 Line 227 142 Line 125 141  Line 126 133 Line 192 142 Line 191 144 Line 194 157 Line  158 156 Line 158 143 Line 168 132 Line 171 131 Line 180  131 Line 183 133 Line 128 128 Extrude 192 128 192 128  44 90 168 147 128 Join One_sided [SEP] [SOL] Line 159  106 Line 195 104 Line 223 130 Line 128 129 Line 194 141  Line 195 142 Line 195 142 Line 197 144 Line 200 150 Line  202 152 Line 152 151 Line 153 145 Line 158 141 Line 174  134 Line 178 133 Line 128 128 Extrude 192 128 192 128  57 83 141 114 128 Cut One_sided [SEP] [EOS]</p>	Geometry	 
Model 1 Page 4 of 5			Please write your rankings (1-8) in the box.

Figure 23. An example model in our questionnaire. (4 of 5)

Input  
Point  
Cloud

Converted CAD Sequences

Rendered  
Geometry

Rankings



[SOL] Circle 176 128 48 [SOL] Arc 170 92 51  
Counterclockwise Line 170 121 Arc 169 122 5  
Counterclockwise Line 139 122 [SOL] Line 169 134  
Arc 170 135 5 Counterclockwise Line 170 164 Arc  
139 134 51 Counterclockwise [SOL] Circle 176 128 3  
[SOL] Arc 212 122 51 Counterclockwise Line 182 122  
Arc 181 121 5 Counterclockwise Line 181 92 [SOL]  
Arc 182 134 5 Counterclockwise Line 212 134 Arc  
181 164 51 Counterclockwise Line 181 135 Extrude  
192 64 192 32 128 128 192 116 128 New\_body  
One\_sided [SEP] [EOS]



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Please write  
your rankings  
(1-8) in the box.

Figure 24. An example model in our questionnaire. (5 of 5)